

# Higher-Order Networks

# So Much Types of Networks

**Networks** help in **representing** and **analysing complex systems**

Chosen **network model depends on the data**

**Temporal Networks, Bipartite Networks, Weighted...**

# Sequential Data and Networks

What about Pathway/Sequential networks ?

**Standard network** model depicts **pairwise interactions**

... sometimes simple models are not meaningful

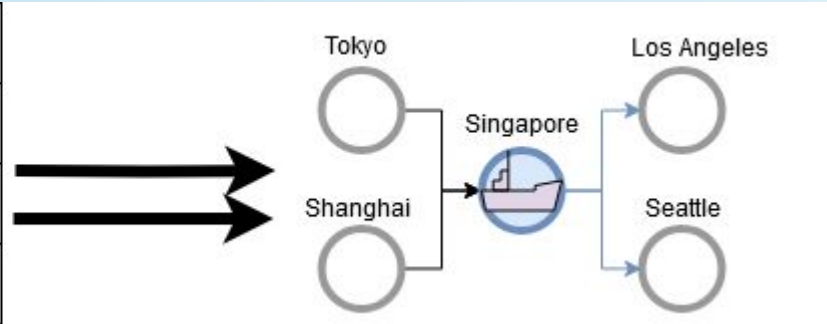
# Sequential Data and Networks

## What about Pathway/Sequential networks ?

Standard network model depicts pairwise interactions

... sometimes simple models are not meaningful

Vessel	Departure	Sailing data	Arrival	Arrival Date
v1	Shanghai	2013/01/01	Singapore	2013/01/15
v1	Singapore	2013/01/16	LA	2013/02/05
v2	Singapore	2013/02/01	LA	2013/03/08

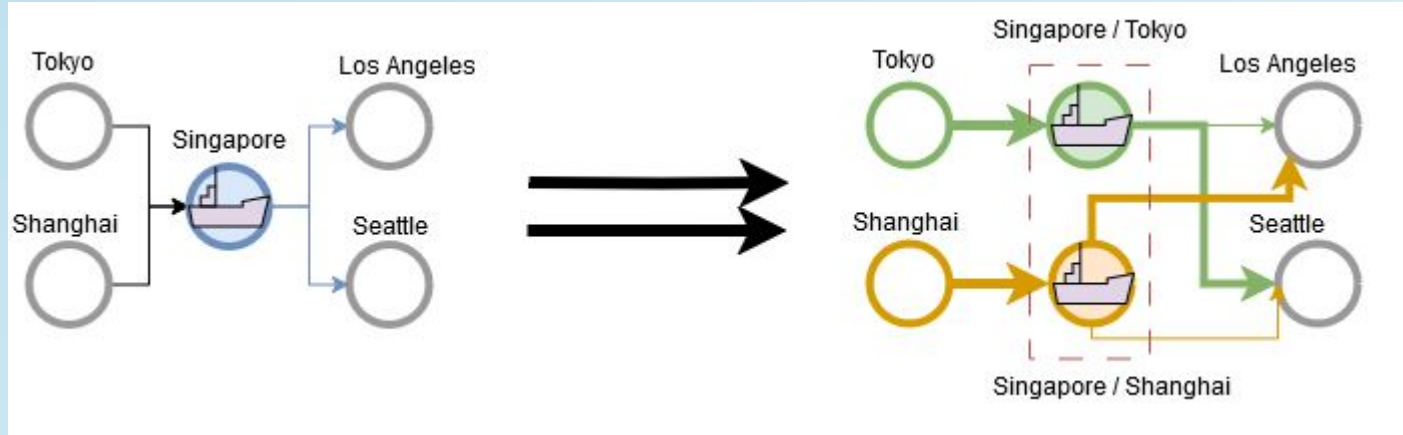


Xu et al. 2016. Representing higher-order dependencies in networks

# Sequential Data and Networks

In case of **trajectories** for instance, **ordering**, long range and **memory of previous states** is important

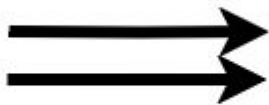
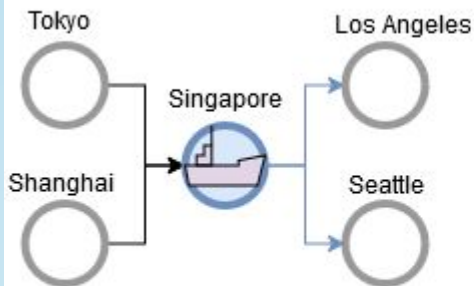
**Vessels** can have **particular destinations** based on **initial ports**



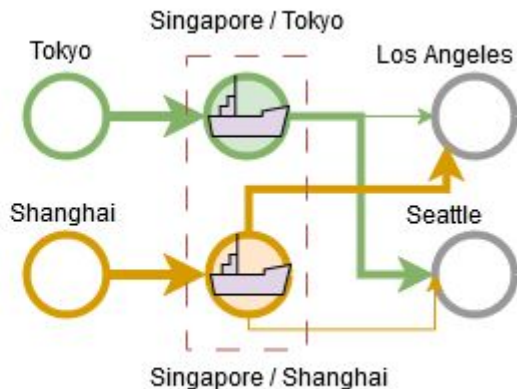
# Sequential Data and Networks

We need to go beyond pairwise interactions

First-Order Representation



Higher-Order Representation



# What are Higher-Order Networks?

**Higher-Order Network (HON) = Network representation**

**Nodes** represent **sequence of states** (memory nodes)

**Edges** represent **transitions** to possible **next states** (transition probabilities)

**Random Walk** through HON = **Non-Markovian process!**

**Many real-world applications: Biological pathways, trajectories, urban traffic, social interactions**

# From Sequences to HON

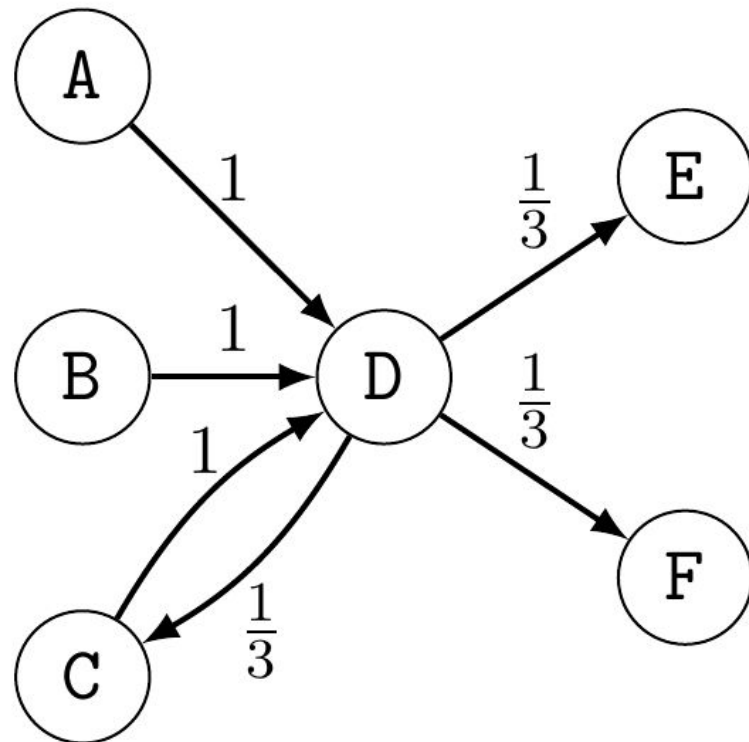
Séquences	#
A D E	2
D E	1
B D E	3
D F	2
B D F	4
B D C	3
C D C	3



# Direct Dependencies are Poor

First-Order Network

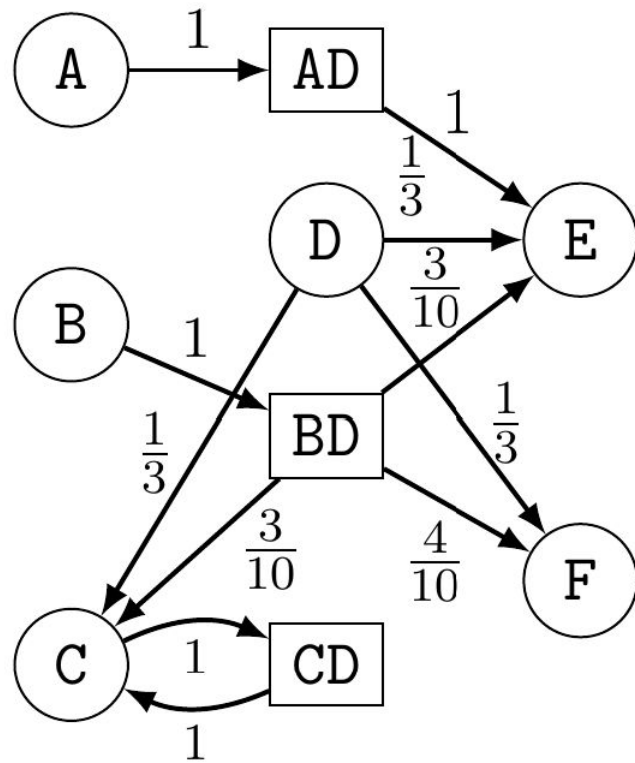
Séquences	#
A D E	2
D E	1
B D E	3
D F	2
B D F	4
B D C	3
C D C	3



# Looking In The Past

Séquences	#
A D E	2
D E	1
B D E	3
D F	2
B D F	4
B D C	3
C D C	3

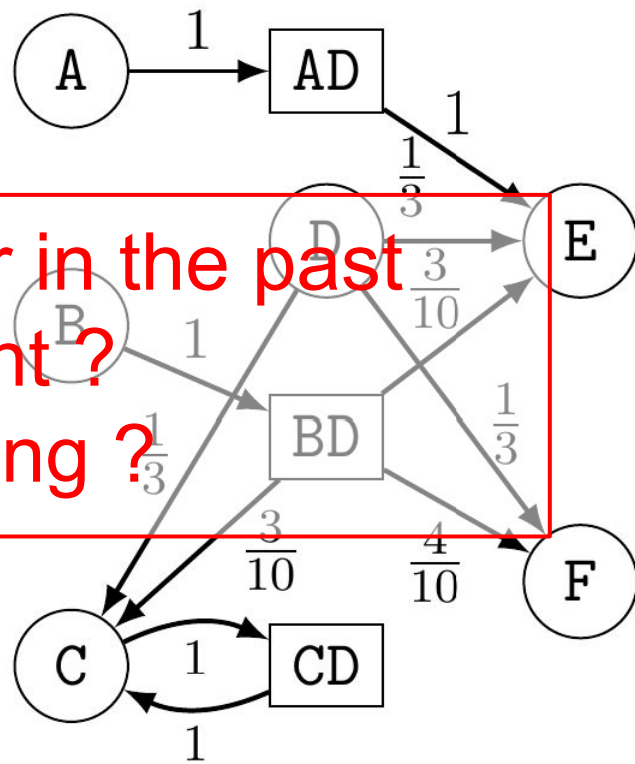
Second-Order Network



# Keep Looking back?

Séquences	#
A D E	2
D E	1
B D E	3
D F	2
B D F	4
B D C	3
C D C	3

Second-Order Network

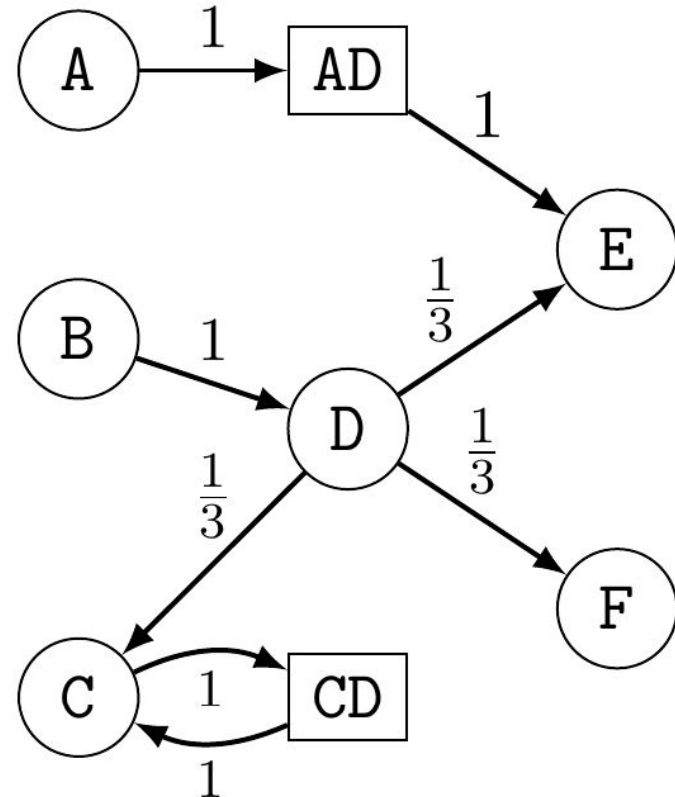


Is going further in the past relevant?  
Overfitting ?

# Not All Past is Relevant

Séquences	#
A D E	2
D E	1
B D E	3
D F	2
B D F	4
B D C	3
C D C	3

Variable-Order Network



# Pros and Cons of HONs

- + Capture **long range interactions** between **sequence elements**
- + Walk through HONs give **better sequence predictions**
- **Larger models**
- Require **sequence mining + counting** (computer cost)
- **What is a node? Maximum order?**

# Definitions

Let  $A$  be the set of all possible states

$\mathcal{S}$  is the multi-set of sequences  $s_i$

with  $s = \sigma_1\sigma_2\cdots\sigma_m$  an ordered sequence of states

Order of  $s$  is noted  $|s| =$  **number of states**

$c(s)$  is the number of occurrence of  $s$  in  $\mathcal{S}$

# Definitions

$s'$  **suffix of**  $s$  iif  $|s'|$  **last elements** of  $s = s'$

$s'$  **prefix of**  $s$  iif  $|s'|$  **first elements** of  $s = s'$

Depending on the sequential model  $s$  can be (statistically) represented by a suffix  $s'$  called context

{AD, ADE, DF} included in S

{AA, DEDF} are not

**E** is a **1st-order** seq

$$c(E) = 6$$

**BD** is a **2nd-order** seq

$$c(BD) = 10$$

Séquences	#
A D E	2
D E	1
B D E	3
D F	2
B D F	4
B D C	3
C D C	3



$$p(BD \rightarrow E) = p(E|BD) = ?$$

Séquences	#
A D E	2
D E	1
B D E	3
D F	2
B D F	4
B D C	3
C D C	3

$p(BD \rightarrow E) = p(E|BD) = ?$

$$P(E|BD) = \frac{c(BDE)}{\sum_{\sigma \in A} c(BD\sigma)}$$

= 3/10

Séquences	#
A D E	2
D E	1
B D E	3
D F	2
B D F	4
B D C	3
C D C	3

# HONs are Stochastic Graphs

$$G = (V, E)$$

$V$  = Set of **memory nodes** being **sequential contexts**

a **node  $v$**  is a **representation of a state** from  **$A$**

Ex: AD is a representation of the state D

*“Arrived at D with A as previous state”*

$E$  = Set of **directed** and **weighted edges**

$$P(\sigma | s) > 0 \text{ associated with } s \rightarrow s^* \sigma$$

# Fixed-Order Network Models

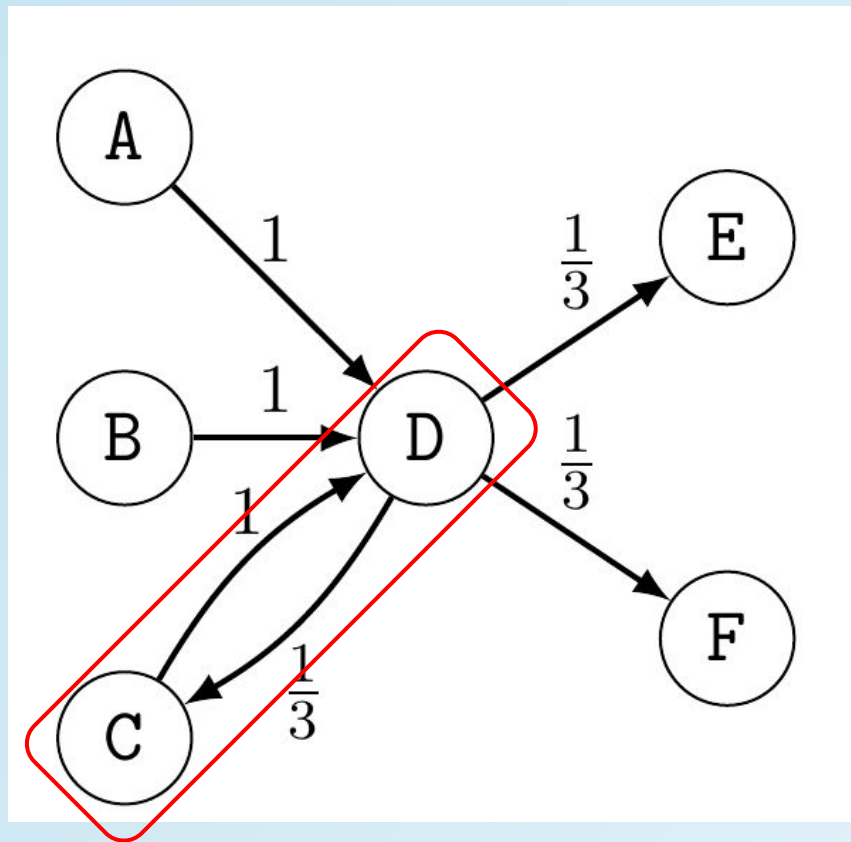
# Fixed-Order Network (FON)

First-order network ( $\text{FON}_1$ )

Contexts of size 1

$$\underline{P(C|CD)} = \underline{P(C|D)} = 1/3$$

$$P(\cdot|D) = [0, 0, 1/3, 0, 1/3, 1/3]$$

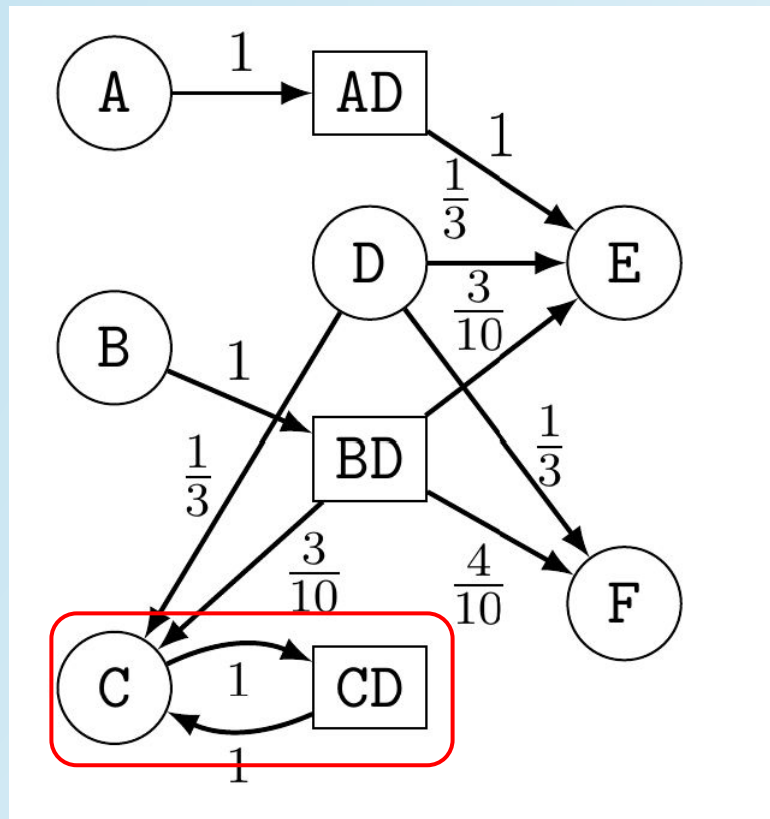


# Fixed-Order Network (FON)

Second-order network  $\text{FON}_2$

Contexts of size 1 and 2

$$\underline{P(C|CD) = 1}$$



# Fixed-Order Network (FON)

Generalisation to  $\text{FON}_k$  possible

... but becomes very large  $\mathcal{O}(N^k)$

... and which  $k$  ?

# FON<sub>k</sub> construction process

1 Contexts are all sequences of size  $\leq k$

2 Adding nodes and edges from considered contexts  $c$  and distributions  $P(\cdot|c)$

Ex: "ADE" in FON<sub>2</sub> gives A -> AD -> E

"DE" gives D->E (E is a stop here)



# Variable-Order Network Model

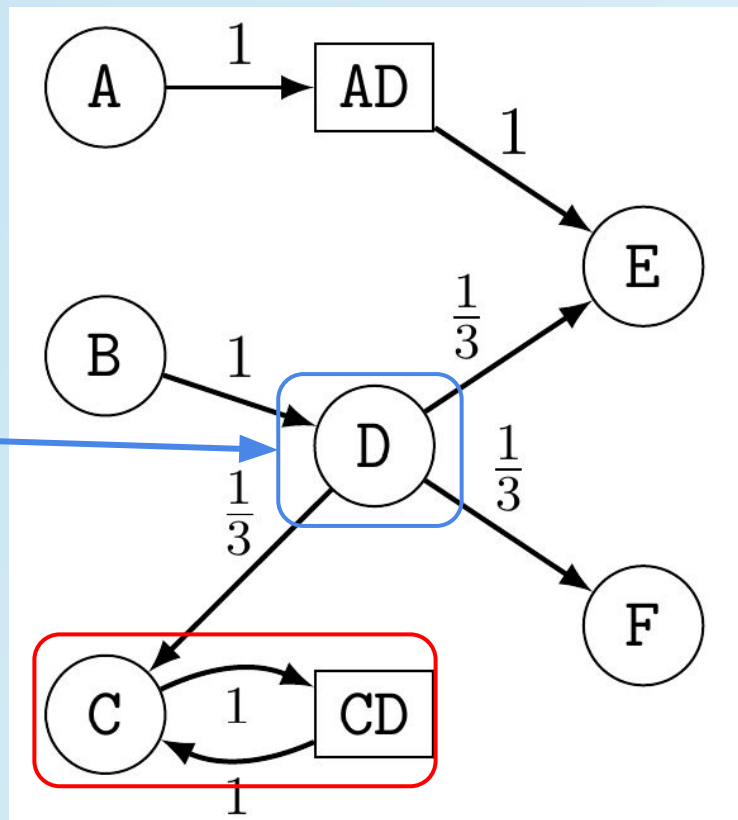
# Variable-Order Network (VON)

Contexts of variable size

$$P(C|CD) = 1$$

Keep only **informative contexts**

Ex:  $P(.|BD)$  similar to  $P(.|D)$



# Variable-Order Network (VON)

Context of **different sizes** are considered

**Statistically relevant contexts** are kept

Use of **quality function!**

The **Kullback-Leibler divergence**  $D_{KL}$

# Variable-Order Network (VON)

The Kullback-Leibler divergence  $D_{KL}$  is a **measure used in information theory**

For a context  $s$ , **let  $Q$  be the distribution  $P(.|s)$  and  $P$  the distribution associated to  $s'$  an extension of  $s$  ( $s$ =suffix of  $s'$ )**

$D_{KL}$  gives the additional information (bits) encoded by  $P$  regarding  $Q$

$$D_{KL}(P||Q) = \sum_{\sigma \in A} P(\sigma) \log_2 \left( \frac{P(\sigma)}{Q(\sigma)} \right)$$

# Variable-Order Network (VON)

Context **relevant** if  $D_{KL} > \text{threshold}$

**Preference** in keeping a **short** and **highly observed** sequence

$$D_{KL}(P||Q) > \frac{|s'|}{\log_2(1 + c(s'))}$$

# VON construction process

- 1 Starts with **first-order context** (elements from  $A$ )
- 2 Context **extension** and  $D_{KL}$  **test**
- 3 **Adding nodes and edges** from considered contexts  $c$  and **distributions**  $P(.|c)$

# Reminders on HONs

FON	VON	Feature
Fixed $k$	Variable	Memory Length
Higher	Lower	Model Complexity
Limited	Better	Scalability

Many other models exist: Tensor based, multi-order network, von-sample..

# Higher-Order Network Analysis



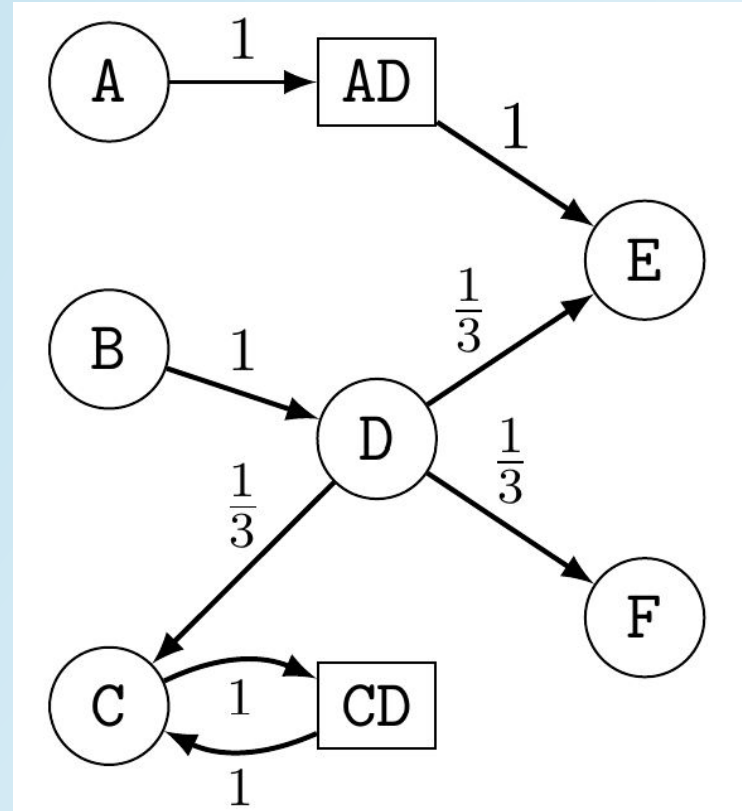
# Analysing HONs

Are standard network analysis tools efficient for HONs?

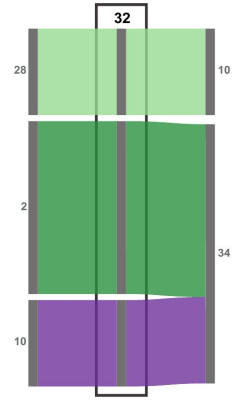
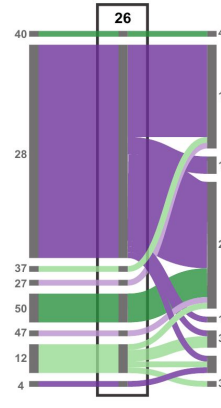
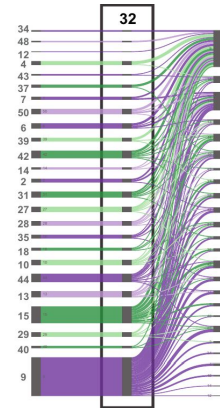
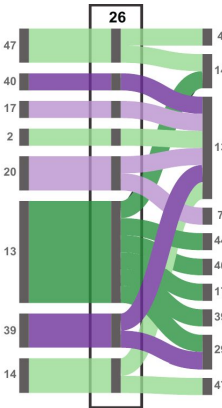
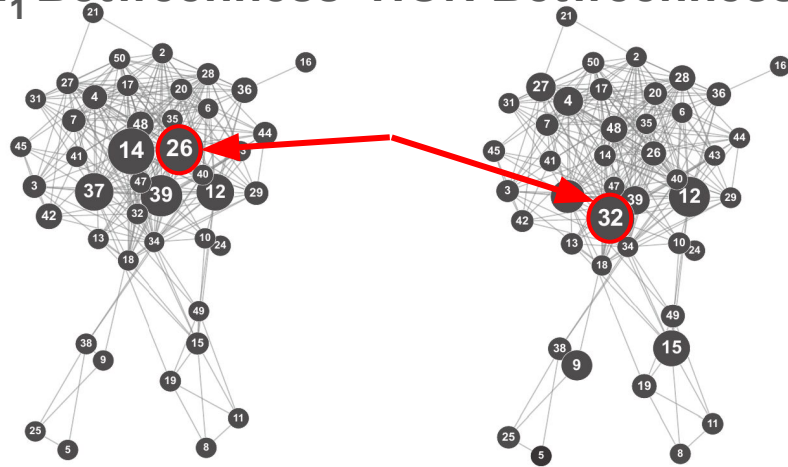
What is a **clique** in HONs?

**Degree?**

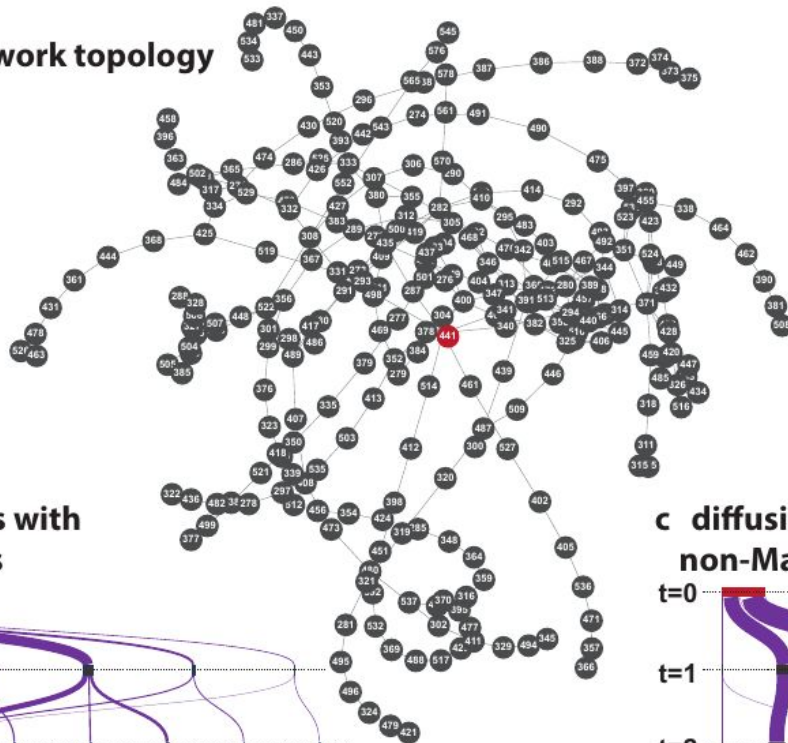
Topology? **Centrality?**



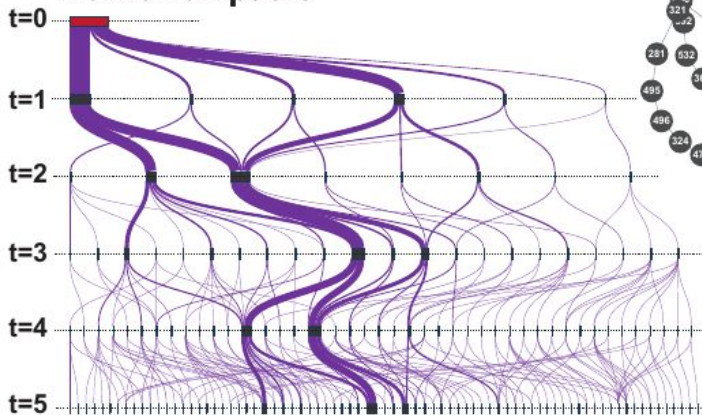
# FON<sub>1</sub> Betweenness HON Betweenness



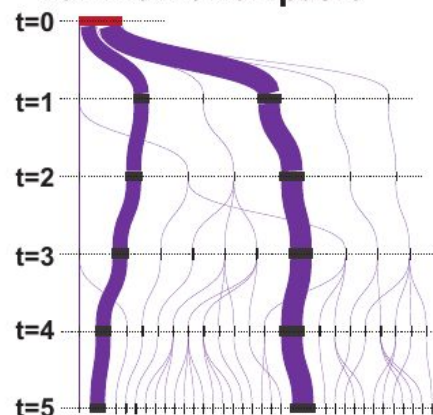
**a network topology**



**b diffusion process with Markovian paths**



**c diffusion process with non-Markovian paths**



# PageRank on HONs

# PageRank on HONs

HONs = Good network model

=> **Analysis Tools** applied on HONs would **give better results!**

(... true ?)

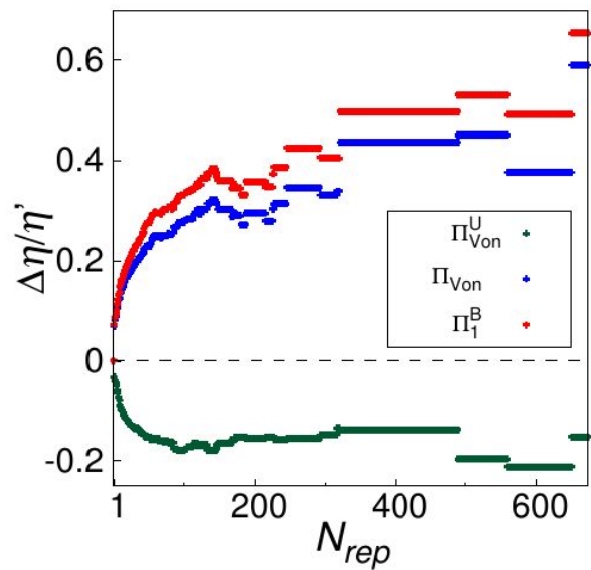
# PageRank on HONs

**Score of state  $\sigma$  is calculated from its representations' scores**

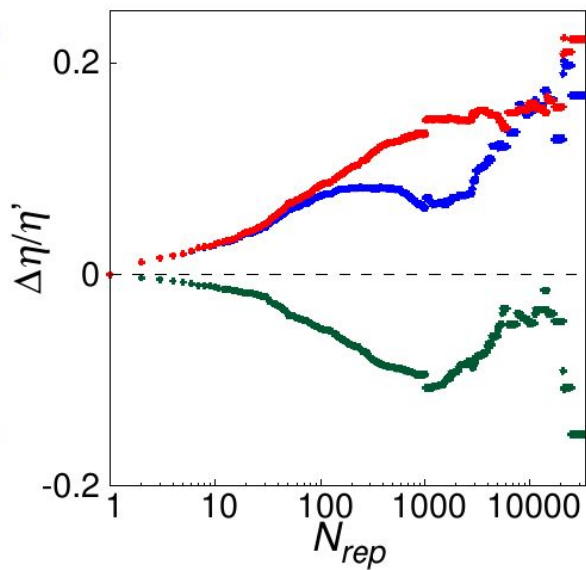
**In case of PageRank, highly represented states can lead to biases**

**Because of standard PageRank algorithm the more a state is represented the more its representations will be visited (due to teleportation)**

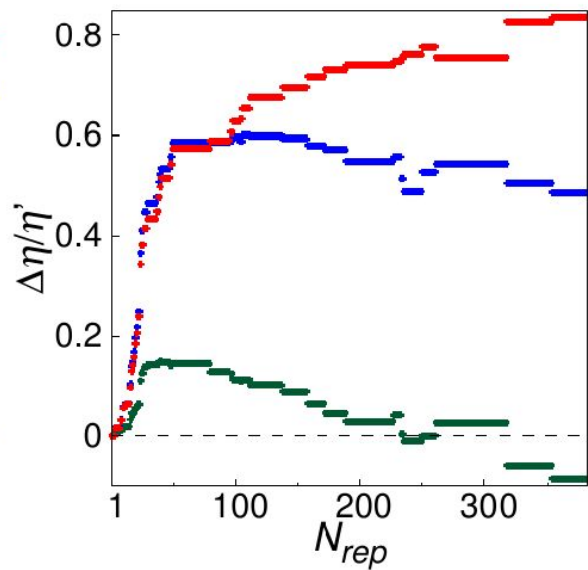
**Need to adapt the tool to HONs**



(a) Maritime



(b) Airports



(c) Taxis

# Additional Notes

The term **Higher-Order Network** is **highly used in the literature**

Most of the research on **pathway networks** use it, but **other usage too**

Among them we have:

**Hypergraphs** (edge between more than 2 nodes)

**K-cliques** analysis

**Simplicial complex**